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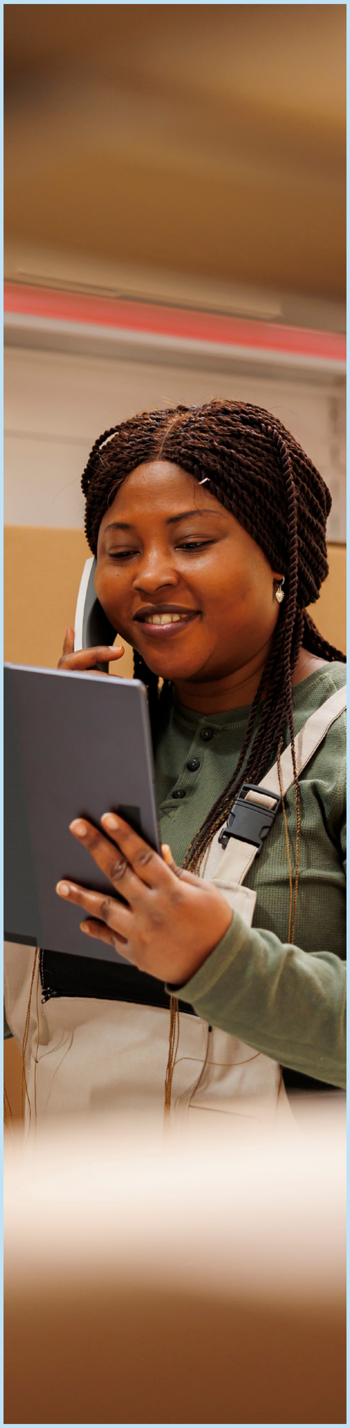

THE ROLE OF PREDICTIVE ANALYTICS IN CATEGORY MANAGEMENT

Abstract

This white paper explores the transformative impact of predictive analytics on category management within the sourcing and procurement value chain. It highlights how predictive analytics can enhance decision-making, optimize category management strategies, and drive cost savings.

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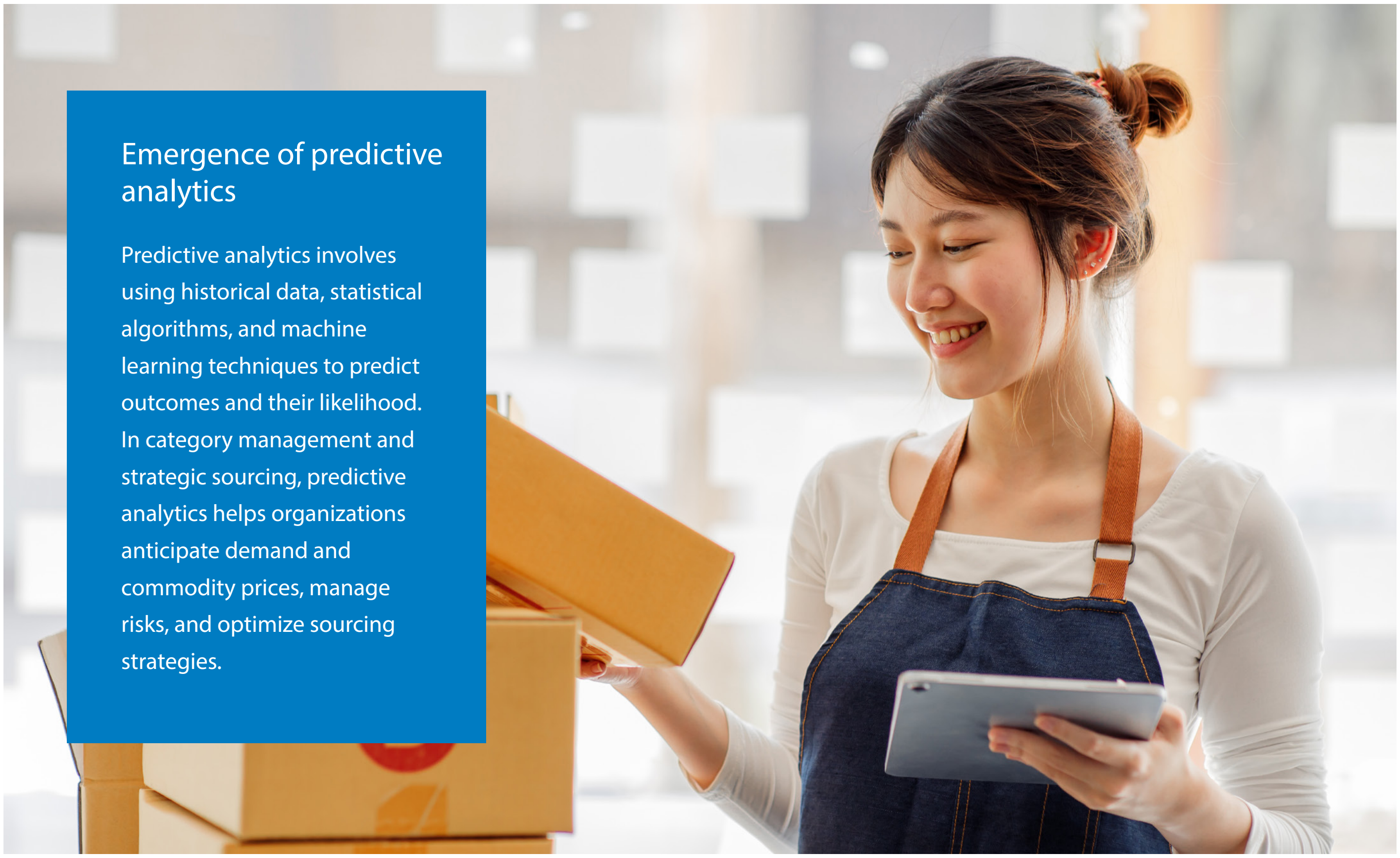
Category management: An overview

Category management is a strategic approach to procurement that segments spend into groups of similar or related products, enabling organizations to focus on specific categories to drive value. It is crucial in the source to pay (S2P) process as it helps streamline procurement activities, improve supplier relationships, and achieve cost efficiencies. Generally, the indirect spend covers categories like IT, professional services, MRO, marketing, facility management, packaging, logistics, etc.



Emergence of predictive analytics

Predictive analytics involves using historical data, statistical algorithms, and machine learning techniques to predict outcomes and their likelihood. In category management and strategic sourcing, predictive analytics helps organizations anticipate demand and commodity prices, manage risks, and optimize sourcing strategies.

The S&P (sourcing & procurement) value chain and its challenges

Key processes in the S&P value chain

The S&P value chain includes various key processes - category management, strategic sourcing, contracting, procurement, supplier & material master management, and supplier management. Category management & strategic sourcing, being the upstream components, are of upmost importance for overall value chain efficiency & effectiveness.

Common challenges

The sheer volume and variety of goods and services being purchased at organizations make the S&P process complex. The volatility and uncertainty of the market adds to the complexity. This exposes S&P to challenges like price volatility, supply continuity risk, supplier risk, cost management, and demand fluctuations. These challenges can lead to inefficiencies, increased costs, and supply chain disruptions.

Predictive analytics: An overview

Definition and components

Predictive analytics in procurement involves collecting data on purchasing patterns, supplier information, and market conditions. It uses statistical models and machine learning (ML) to identify trends and patterns to forecast future outcomes. Different types of ML algorithms - supervised, unsupervised, deep, and reinforcement learning are used.

In supervised learning, a dependent variable is predicted or classified in groups using independent variables, whereas the unsupervised learning focuses on classification using only independent variables.

For building AI/ML models, the historical data is split into 3 sets - training, validation, and test. Post data cleansing, The AI/ML model is trained on the training dataset using applicable ML algorithms. Then the validation set is used to check model performance on unseen data during training phase and to perform further hyper-tuning of parameters. The trained and validated models are tested and compared on test set and model with best accuracy is selected. The time series forecasting requires additional steps like ensuring stationarity.

The ML model can then be used for predicting either the values of desired variables based on independent variables or for classification.

Applications

Predictive analytics is used across industries and processes to improve decision-making, optimize operations, and enhance customer experiences. In S&P, it helps primarily in commodity price forecasting, demand forecasting, supplier risk management, and cost optimization. Predictive analytics enables data-driven decisions by providing insights into purchasing patterns and market trends. This helps procurement teams make informed decisions about sourcing and supplier selection.

Predictive analytics use cases in category management

Commodity price forecasting

Variations in commodity prices result in uncertainty in the profit margin of the finished product. Failure to manage increases in cost leads to higher pricing of end products, which may decrease demand. A commodity price forecasting model can come handy to mitigate this risk.

Parameters which are generally used to predict commodity prices are: Macroeconomic & geopolitical uncertainty indices, share market indices (observable market fluctuations), industrial energy source prices (oil, natural gas, coal), world development indicators (e.g. GDP growth rate, exchange rates, consumer industry growth rate), central bank policy parameters (repo rate, etc.,) and commodity's own past price trends and seasonality.

Though standard time series forecasting algorithms like SARIMAX, TBATS, etc., are available, deep learning neural networks like LSTM, Prophet, etc., are preferred for such use cases to obtain high accuracy, multistep time series forecast. The model needs to be retrained regularly based on recent data to maintain accuracy and capture latest market fluctuations.

The predicted commodity prices can be used for strategic decision-making to proactively minimize the impact of price volatility.

The major decision points answered by such predictions are:

- Whether to buy commodities through future contracts or from the spot market
- In case of future contracts, what would be the right time to settle contract to maximize hedging gains
- In case of spot market, in which weeks prices are expected to be at their lowest

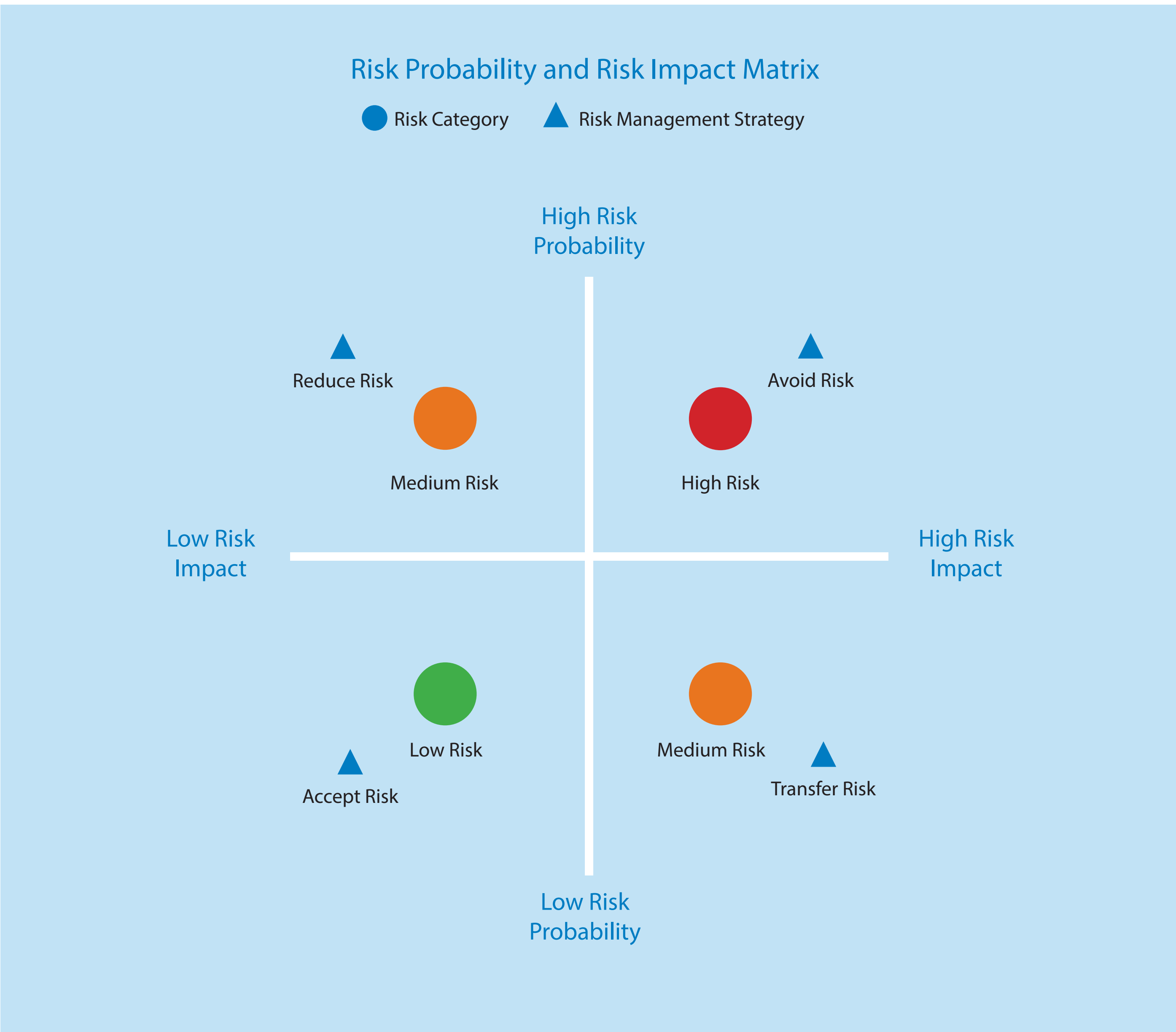
Supplier risk prediction

Lack of awareness of supplier risks cause firms to partner with high-risk suppliers. Predictive models can predict supplier risks more accurately for better supplier selection for new sourcing. Post sourcing, it can help in proactive risk identification and mitigation.

Supervised classification algorithms like Random Forest, Logistic regression, etc., can predict risk probability considering various supplier risk dimensions, such as operational risks (past delivery, quality performance), legal and regulatory risks, financial risks, geopolitical risks, ESG risks, monopoly/overreliance risks, logistical risks, supply chain tier risks, and capacity risks. These risk indicators can be fetched from 3rd party supplier risk tools or can be based on customized logics using relevant raw data. Sentiment analysis of live news can also be used as an input.

Risk impact can be assessed as a function of material category and importance, open PO spend with supplier, etc. Risk rating is calculated as a product of risk probability and risk impact. Based on risk rating, suppliers can be classified in high risk, medium risk, and low risk categories.

The TARA risk management framework shall be used for effective risk management. TARA stands for "Transfer, Avoid, Reduce & Accept Risk". The matrix for identifying supplier risk category and appropriate risk management strategy are given below:



The indicative tactical actions for various risk management strategies are:

Strategy	Post-sourcing	Pre-sourcing
Accept risk	Monitoring	Continue with existing suppliers
Transfer risk	1. Proactive expediting 2. Advance intimation to end user to have a contingency plan 3. Insurance/BGs, indemnity	1. Identify alternate suppliers with low risk scores. 2. Stringent contractual clauses to recover damages- PBG, insurance/BGs, indemnity
Reduce risk	1. Proactive expediting, 2. Review inventory levels/options to increase safety stock 3. Market scanning for alternate suppliers for new orders in future 4. Advance intimation to end user to have a contingency plan	1. Identify alternate suppliers with low risk scores 2. Split orders 3. Stringent contractual clauses to recover damages - PBG 4. Stringent approval matrix
Avoid risk	Cancel PO or take one-time delivery, return to market for alternate supplier discovery	Reject vendor & Scan market for a new low-risk supplier

As seen above, by using supplier risk prediction models & robust risk management framework, S&P teams can proactively manage potential disruptions.

Spend classification

The two main issues with spend classification are incomplete material descriptions and lack of adoption of standardized classification systems. Material descriptions in material master and free text requisitions are often incomplete and thus makes it difficult for their classification to correct categories. On the other hand, standard classification systems like UNSPSC are not used widely. Usage of client custom taxonomy (which sometimes even vary across departments) brings ambiguity in definition & coverage of each category, making accurate classification more challenging.

Inaccurate spend classification reduces visibility into spending patterns, making it difficult to monitor and control expenses. Without a clear understanding of where money is being spent, it's difficult to identify cost-saving opportunities.

Inaccurate classification can weaken an organization's ability to negotiate. It becomes harder to leverage volume discounts or identify preferred suppliers. Ultimately this can lead to misguided decisions regarding budgeting, procurement, and supplier negotiations.

Predictive analytics can predict the spend category for each item with high accuracy, or in simple words it can classify the spend in defined categories. The prediction of spend category is based on features like item description, item name, supplier name, etc. The spend classification utilizes natural language processing (NLP). The TF-IDF (term frequency-inverse document frequency) is used to convert words into numerical vectors for text mining and retrieval.

Post formation of these vector matrices, stand-alone multi-label classifier models like: Linear SVC, Extra Trees, and One Vs Rest Logic are used to predict spend category. Finally, to make classification very robust and accurate, ensemble model is used (i.e., weighted average of probabilities predicted by standalone models is used to predict final probability for a spend category).

The other way is to utilize LLMs which can analyze large volumes of text data from invoices, purchase orders, and other procurement documents. They can identify patterns and categorize spend data according to the customized taxonomy. For this, LLMs can be trained on specific taxonomies provided by the client. This involves using historical spend data to teach the model about how to classify new data accurately.

Demand forecasting

Predictive analytics is used in forecasting demand of finished goods by end customers. For efficient procurement, it's also necessary to estimate quantity of materials to be bought. Material requirements planning (MRP) is used to find requirement of direct materials and to plan their purchase accordingly. On the other hand, forecasting indirect spend specifically for categories like MRO (maintenance, repair, and operational supplies) is a complex problem. Forecasting MRO item demand is crucial for:

Inventory optimization

Organizations can achieve significant cost savings by optimizing their sourcing strategies and negotiating better contracts with suppliers based on predictive insights.

Cost optimization

By predicting accurate demand, companies can avoid unnecessary purchases thus reducing holding cost.

Reduced downtime

Maintaining proper inventory level ensures the availability of necessary MRO items which minimizes downtime and keeps operations running smoothly.

Better supplier negotiations

Forecasting gives the correct volume of goods to be purchased, which helps in better planning of delivery schedules to ensure timely deliveries and better negotiations with suppliers through volume discounts and favorable terms.

Machine Learning algorithms like Multiple Regression, Support Vector Machine, Random Forest, etc., are useful in building predictive models for forecasting demand and corresponding category spend. The features to be used for predicting demand and spend are planned production volumes, revenue target, commodity price indices, past demand trend, etc.

Benefits of predictive analytics in S&P

Cost savings

Organizations can achieve significant cost savings by optimizing their sourcing strategies and negotiating better contracts with suppliers based on predictive insights.

Enhanced supplier performance

By identifying potential risks, predictive analytics helps mitigate risks proactively and ensure better supplier performance.

Improved efficiency

Predictive analytics streamlines the S&P process by providing actionable insights that enhance decision-making and operational efficiency.

Challenges and considerations

Data quality and integration

High-quality data and seamless integration are crucial for the success of predictive analytics in procurement. Before using data for model training, comprehensive data cleaning is required which includes handling missing values, outliers, and duplicates; data normalization; encoding categorical variables; and feature engineering.

Responsible AI considerations

Ensuring the ethical use of data and algorithms is essential. It shall be ensured that AI systems/ML models are fair, transparent, accountable, and ethical. Data privacy and security shall be taken care of.

Conclusion

Summary of key points

AI/ML-powered predictive analytics is invaluable for forecasting variable values and solving classification problems. In today's volatile and uncertain markets, these applications are essential as S&P grapples with rising costs and supply continuity risks. Within S&P, predictive analytics is leveraged for commodity price forecasting, demand forecasting, supplier risk management, and cost optimization. It plays a pivotal role in category management by enhancing decision-making, optimizing sourcing strategies, minimizing supply risks, and driving cost savings.

Call to action

Organizations should adopt predictive analytics to stay competitive and enhance efficiency in their S&P processes. This approach enables data-driven decisions, valuable insights, and proactive challenge management, essential for thriving in today's dynamic market.

Author

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Avinash leads the S&P DTS Practice at Infosys BPM. He comes with more than 20 years of experience in sourcing & procurement and supply chain in core industries and consulting/shared services firms having led various transformation initiatives controlling cost and Procurement budgets. At Infosys BPM he is responsible for digital revenue generation, new solutions development, and delivery for multi-country clients.

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